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An overview of Markov Chains for monitoring indoor movements and ambient motion detection

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Abstract

Background: In recent years and due to the availability of non-wearable sensing technologies, there has been a widespread interest in developing methods for monitoring the movements of older adults and further estimating any anomalies.
Objective: Low-cost motion detection has been gaining particular attention due to its widespread availability, ease of deployment, and inherent property in protecting privacy. In addition, and due to the cost-benefits, it has become an attractive alternative for the low-income sector of society. This paper presents an overview of a monitoring framework and a review of the literature using motion detection sensors.
Method: Markov Chains (MC) have been explored by many researchers as a suitable framework for monitoring and estimating sequences of events associated with movements and activities which can further be used as a part of an anomaly detection system in a sensor network. This paper presents an overview of this method and related literature.
Results: A brief overview of MC and the related literature with some insights and challenges associated with the potential limitations and future extensions. One of the challenges of utilizing MC is the definition of what can be considered the state of movements and activities and what can be used as a measure of such state. In this context, various extensions of MC have been utilized where the state of the system can not be measured directly and are defined in a form of Hidden Markov Models (HMM).
Conclusion: Proper deployment of motion detection sensors and associated MC for monitoring requires an in-depth understanding and co-designing of the system with the family members, care providers, and engineers in order to fully take advantage of such technology. Depending on the number and properties of the selected sensors (such as their effective range and the inherent time delay), particular attention needs to be paid to what can constitute a measurable (observable) state and what can be further defined as a hidden state.

Keywords: Markov Chains (MC), movement monitoring, ambient motion detection, Hidden Markov Model (HMM)

Introduction

Monitoring the movements of older adults is one of the most elementary but important features in support of Aging-In-Place (AIP). It is a term that has recently been used in reference to alternative lifestyle support that can be made available to the aging population that is now being better realized through the availability of sensing and AI technologies (Aging in Place, 2020; Thinking about Aging in Place, 2020). The early entry to this augmented lifestyle is also better realized by the older adults who are still in relatively good physical and mental health and still prefer to live independently in their place of residence. Most importantly and due to complexities associated with the determination of any onset of anomalies in movements and activities, the earliest definition of which can be considered as a healthy baseline of data can facilitate the efficiency for any future anomaly predictions. In addition, such a monitoring environment may also have the potential to support various levels of self-rehabilitation or interventions such as physical activities or patient-regulated exercises (Tijsen et al., 2019).

Currently, there exists a wide range of sensors that can be deployed in support of AIP (Chen et al., 2012; Cook, 2020). Some examples of the type of common sensors which are employed as a part of monitoring and assistance are: ambient (e.g. passive infrared motion sensor, contact switches), wearable (e.g. accelerometer, RFID, EEG), and high-dimensional ambient sensors (e.g. camera, thermal, microphone, RFID, WiFi). Some of the behavior markers that can be extracted from the sensor data are mobility, exercise, sleep, activity, environment, devices, socialization, and circadian and diurnal rhythms. Perhaps the most prevalent behavior metric is movement.

Recently and due to the availability and affordability of off-the-shelf monitoring sensors (such

Figure 1. An example of a layout of a living place. It is assumed that the number of rooms and their arrangements can take various forms (Curtesy of dreamstime.com)

as motion detection), it is increasingly possible to instrument the living environment with various such ambient sensors. The number, type, and distribution of these sensors are dependent on many factors and may need to be co-deployed and implemented with the assistance of the resident older adult (Summer et al., 2020). Factors such as cost, privacy level, placement, and resolution are some of the main points that can be included in the early stages of the decision-making. In addition, processing the recorded information obtained through these sensors for arriving at some meaningful conclusions requires careful data management and interpretation, which also must take into account individual lifestyles and their current general state of mobility and health conditions. This can further assist in establishing a baseline from which future interpretation of the tracking data can be compared.

Markov Chain and its various extensions have been utilized in various applications which involve decision-making given sequences of observation. It has been identified as one of the formal frameworks to interpret the data resulting from current and past recorded events. In this paper, we present some motivations and an overview of this framework, and a further summary of some of the recently published results related to the monitoring of movements and activities of older adults. In general, monitoring of movements and activities of older adults in relation to establishing a science for analyzing and predicting various onsets of anomalies based on the sensed information can be distributed into different levels (Payandeh 2018) (Bharadwaj et al., 2014). In this paper, we focus only on applications where ambient sensing technologies can be deployed in living spaces and in particular the application of motion detection sensors. This technology offers a coarse measure of the movements but more importantly, they have the highest level of privacy protection (i.e. they only detect the presence or absence of movements in their field of view). However, due to this coarseness in their measurements, their wide field of view, a time delay between their activation and deactivation in relation to their placement in a living space (*Figure 1*), and their integration with the monitoring algorithms need to be properly synthesized.

Markov Chains (MC)

To better present and motivate the application of MC for monitoring indoor movements and activities, we will first idealize and demonstrate the overall objectives of monitoring using a simple example. In this example, we assume that a person is walking along a corridor following a sinusoidal trajectory (Appendix, *Figure A1*). Along the path of this trajectory, we also assume that there are several sensors mounted on the floor that are distributed along the path. We further assume that these sensors are only activated when the person is exactly on top of them.

Using this example, we further utilize some basic definitions from signal reconstruction to describe the challenges associated with estimating the actual trajectory of the person (i.e. the sinusoidal path) when the number of these sensors is reduced. As it can be seen in *Figure A1*, when the number of sensors is reduced, the estimated trajectory of the person resembles less the actual trajectory.

In the above hypothetical example, one can also utilize various other sensing modalities to measure the position of the person which can be used for further trajectory estimation. These sensing modalities can be categorized as ambient or wearable. However, regardless of the sensing technology, the following assumptions are usually applied: (a) distributed sensors can measure the location of the person at the designated location; (b) the motion detection sensors do not have any measurement overlap with each other that can cause interference in measurements; (c) there is no presence of noise in the measurements that can cause further uncertainty in a trajectory estimation; and (d) sensors are placed at exact locations where the movements occur.

Depending on the objectives of movement tracking, the interpretation and accuracy of the sensed data for trajectory reconstruction are dependent on the number and type of sensors. For example, most available motion detection sensors have an inherent time delay in their response which can further complicate the accuracy of the trajectory reconstruction. Even if one utilizes more accurate measurements of the trajectory by employing more expensive wearable sensors (such as ultra-wideband wireless motion sensors), one still needs to deal with the compounded time

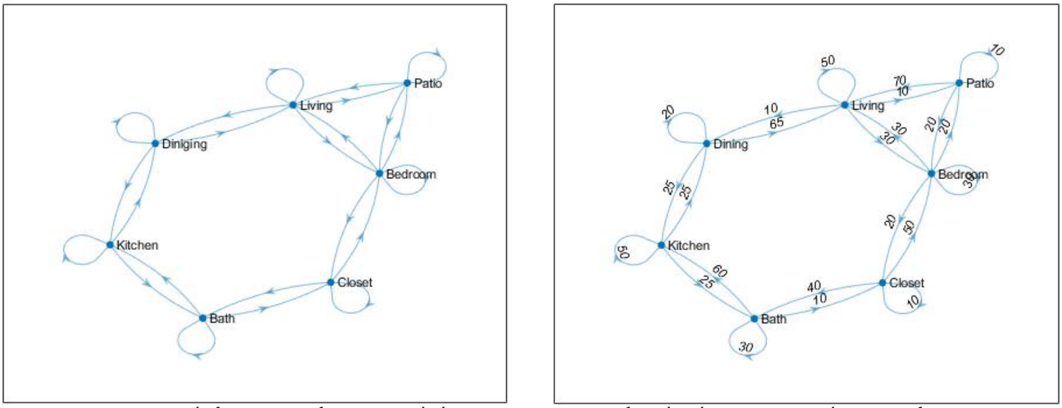

Figure 2. Various definitions of state and their propagation for the living-space layout of Figure 1. (2a - left) shows the directed graph where the state is defined as presence or absence in various areas of the living space and (2b - right) shows an example of conditional probability distributions of moving between the states. The number beside each arrow shows the probability of being at the state defined by the head of the arrow, conditioned on the state defined by the tail of the arrow.

delay that contributes to inaccuracies in measurements. Another approach for increasing the accuracy of movement measurements is through the utilization of ceiling-mounted cameras. This alternative approach can increase the cost associated with their deployment and further analysis of the results, and also may reduce the level of privacy protection of the occupants (Dai et al., 2013; Kearns et al. 2017). For the case of wearable sensors proposed by (Yaremych et al., 2019), some level of privacy protection can be introduced such as masking the identity of the tracked person to a digital signature which can be tracked in tasks such as those associated with their food selection preferences.

Full Markov Models (MM)

Markov chain (or Markov process) is a representation for propagation between various discrete events such as discrete positions (or states) along a movement trajectory of a person along a path (Sucar 2015). It is stochastic modeling where the propagation between the states is represented by probability distributions. As such, the representation is constructed by observing the process (i.e. movements and activities of older adults in a dwelling), over a predefined observation period for defining the conditional probabilities of propagation between the predefined states. This is also referred to as the state transition description (or diagram).

One of the design challenges of utilizing the Markov Chain is knowing how the events or states of the system should be defined. For example, referring to the living-space layout shown in *Figure 1*, we can define the presence or absence of a person in various areas, such as in the Dining Room, Living Room, Patio, Kitchen, Bathroom, and Closet as the state of the Markov chain. Let us assume that for a given window of observation (i.e. time of the day, period of recording, or the number of recording periods over a week or months (Payandeh et al., 2019a; Payandeh et al., 2019b), we can determine the movement distributions (or state propagation) between various areas (or states). These distributions are represented by the directional arrows pointing between various locations (i.e. a directed cyclic graph representation (*Figure 2a*). Each arrow designates the conditional dependency of the current state (the head of the arrow) based on the previous state (the tail of the arrow). These conditional dependencies are represented by probability values shown beside each arrow (*Figure 2b*).

One requirement on this directed cyclic graph is that the sum of the probability values for propagating from a given state to the next state needs to add up to 100 (for a given window of the observation). The process of enforcing this requirement is referred to as the normalization step for the accumulated amount of data during the window of observation (*Table 1*).

The graph model of *Figure 2b* can be used as a model for further interpretation of sequences of conditional probabilities. For example, from the diagram one can observe that there is a 30% probability that the tracked person is in the dining room given that the person was previously observed to be in the Living room. Such representation can be used to predict the joint probability of a sequence of transitions between the states. This feature would be one of the applications of the Markov Chain for the proposed monitoring process. Given the Markov Chain Model for the observation window and the prior probability distribution of a person being in any of the rooms, we can ask a prediction question based on the observation. For example, given that a person was previously in various connected

Table 1. An example of conditional probability definitions between various states of the Markov Chain (Figure 2b). Distributions are assumed to be computed for a given observation window, e.g. a period of the day over several days.

	Kitchen	Dinging Room	Living Room	Patio	Bathroom	Closet	Bedroom
Kitchen	50	25	0.	0.	25	0.	0.
Dinging Room	25	10	65	0.	0.	0.	0.
Living Room	0.	10	50	10	0.	0.	30
Patio	0.	0.	70	10	0.	0.	20
Bathroom	60	0.	0.	0.	30	10	0
Closet	0.	0.	0.	0.	40	10	50
Bedroom	0.	0.	30	20	0.	20	30

rooms, e.g. a sequence of Kitchen, Dining Room, and Living Room, what would be the probability of the person being in the Bedroom next? The probability (p) of the sequence of events between the state of the system is represented by the weight associated with each of the edges of the graph. If we want to predict the probability of the occurrence of the future state, we only need to know the occurrence of each of the states and the conditional probability of the occurrence of each of the child nodes on the graph to its parent node. Referring to *Figure 2*, our system comprises n=7 states (X_n, n = 1,7), we can define the probability of a sequence of a person being in various rooms as:

$$\begin{aligned}
p(x_1,x_2,\cdots,x_n) &= p(x_n \mid x_1,x_2,\cdots,x_{n-1})p(x_1,x_2,\cdots,x_{n-1}) \\
&= p(x_n \mid x_{n-1})p(x_1,x_2,\cdots,x_{n-1}) = \cdots \\
&= p(x_n \mid x_{n-1})p(x_{n-1} \mid x_{n-2})\cdots p(x_2 \mid x_1)p(x_1) \\
&= p(x_1)\prod_{i=2}^{n} p(x_i \mid x_{i-1})
\end{aligned} \tag{1}$$

The above equation is referred to as the Markov property (first-order since each state's child node is only conditioned on its immediate parent node). Besides predicting future states, the Markov chain can be used to learn statistics of sequential data (He et al., 2016) and recognize patterns that are considered to be a part of the data-mining problem. This is also referred to as the supervised discovery of recurrent patterns (Fink 2014). For the above example, a pattern can be searched for the occurrence of the sequence: Living, Bed, Bath, Living, Bed, Bath.

Another application such as where it is known that a sequence of events has occurred (i.e. person was in Kitchen, Dining, Living pattern) and one wants to discover the probability of occurrence of a certain known state which can follow the current pattern, we can follow the description of equation (1) to compute such probability as:

$$\begin{aligned}
&p(Kitchen, Dining, Living, Bed) = \\
&p(Bed \mid Living)p(Living \mid Dining)p(Dining \mid Kitchen)p(Kitchen) = \\
&(0.30)(0.10)(0.25)(0.30) = 0.002
\end{aligned}$$

The above process is also referred to as unsupervised learning. It is also assumed that we have a motion sensor located in the middle of each monitoring area where each sensor has a certain sensing range. For example, here a single sensor can have coverage that matches the size of the monitoring room and is able to detect the presence or absence of a person. We also assume that there are no interferences between the sensors located in each of the monitoring areas.

Hidden Markov Model (HMM)

In Markov Chains (or the Markov Decision process), states which are defined as part of the modeling process are assumed to be visible (i.e. measurable or observable) (i.e. visible Markov Model). In the above example, we define the state of the monitoring process as shown in *Figure 2* by the presence in the Kitchen (state=kitchen) as detected by the kitchen motion detection sensor.

The Markov Chain described in the previous section can also be interpreted as a modeling process to capture the movements/activities of a person who has created the monitoring information and who is also guided by their predefined purpose. As such, the person has control over what state is to be occupied during the monitoring process. For example, if the person's state is detected to be the Living Room, their condition of being in the Living Room is guided by the type of activities that they are to perform (e.g. the state of activities of say watching TV, reading a book, or lying down). As it can be seen, within the previously defined state of the person being in the Living room, there are also embedded states which can represent the person's activities. As such, a Markov Chain can be used to model the activity of the person in the Living Room. However, the states representing these activities cannot be measured directly using only the motion detection sensor located in the Living Room. The state representing the activities of the person can only be interpreted from the presence of the person in the room and the duration.

Such a modeling approach is referred to as the Partially Observable Markov Decision Process (POMDP). It represents a Markov process where the state and the measurements (sensing) are decoupled (Littman 2009). *Figure 3a* shows schematically an example of the definition of the internal state of the person within the Living room. As it can be seen, while in the Living Room, the person follows their own movement transition model between the unobservable activity states which are only partially observable by the motion detection sensor located in the Living room. *Figure 3a* is only a partial representation where the transition from the activities to the neighboring rooms is not shown. This variation of the Markov chain can be used to create an interactive system where one can modify the transitions between various unobservable states through intervention.

Hidden Markov Modal (HMM) is a variation of the Partially Observable Markov Chain where through observation, one can passively estimate the probability of the hidden state (e.g. activities) (Rabiner 1989). For example, *Figure 3b* shows the two states of activities in the living room which are from *Figure 3a*, namely Reading and Watching TV. The graph also shows two observations which are the observation/measurement of the presence of the person by two motion detection sensors namely the Living Room and the Dining Room sensors. The graph of *Figure 3b* also shows the interferences between the measurements of the two sensors depending on the state of activities in the Living Room (i.e. there exists a probability that the activities in the Living Room can be sensed by the two sensors). The question that can be asked for an example, is given the probability of the sequence of measurement/observation Z_i, namely measurements through Living Room and Dining Room motion detection sensors and the Markov chain associated with the activities in the Living Room, what is the probability of a next activity X_i given the previous sequence of activities and measurements in the Living Room? This probability can be computed through the following relationship:

$$p(x_1,\cdots,x_n \mid z_1,\cdots z_n) \propto \underbrace{p(x_1)\prod_{i=1}^{n} p(z_i \mid x_i)\prod_{i=2}^{n} p(x_i \mid x_{i-1})} \qquad (2)$$

In general, there exists a variety of algorithms such as the Viterbi algorithm (Rabiner 1989) that can be used to indicate the most probable sequence of activities (Viterbi path) which are the hidden states of the monitoring area given the sequence of observations through sensors (such as a motion sensor).

Literature review

Following the general description of the Markov Chain (MC), this section presents an overview of some of the related literature on the application of the Markov Chain and HMM for monitoring the movements and activities of older adults. Attention has been given to specifics of how both observable and hidden states are defined and the type of measurements that were utilized.

One of the earliest results which suggest the application of the Markov Chain to model human behavior is presented in (Matsumoto et al., 2003). They have experimentally demonstrated that human behavior can be regarded as probabilistic finite automata using a state transition model like the Markov Chain. For example, authors have divided the habitat of humans into sequences of actions as a function of time. The propagation between the actions (states) is represented by a probability model. Using such a probabilistic model and a given time of observation, they then establish a searching algorithm where they can investigate the detection of non-habitual human behavior. This is done by investigating and

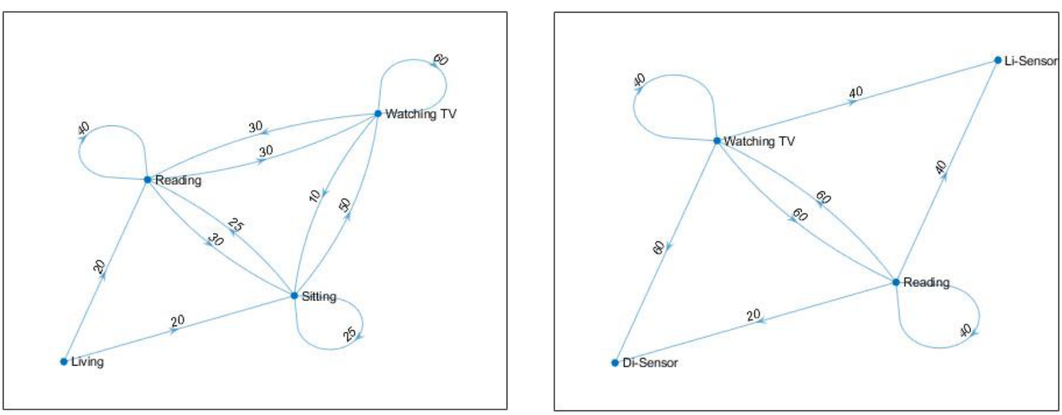

Figure 3. (a) Part of the Markov chain showing example states and transition dynamics which are partially observable through the Living Room motion sensor. Motion activation and the duration can be used as part of the partial observation. (b) an example of a hidden Markov model where the hidden activities were observed through the interference of motion sensor measurements.

identifying the conditional probability for propagation from a given state to any other state which can result in a zero or non-zero value within the window of observation.

Boger et al. (2005) proposed a sequential decision-theoretic model of interaction based on the Partially Observable Markov Decision Process. The authors describe that such a model should be applied to a specific activity (such as washing hands) as a part of the monitoring of an older adult. They endorse that POMDP provides the best formal framework for modeling the decision process. POMDPs allow one to model imprecise information about the current state of the environment, uncertainty in the effects of actions and managing multiple and conflicting objectives. They used a camera as a source of measurement for observing an event. They also incorporated prompts to guide the user during the execution of a task, such as the use of an audio prompt. Such guidance can be used to better explore rewarding scenarios where the monitoring system can also be used as a part of a mentoring system. In their case study, they have defined 20 actions associated with handwashing such as water on/of and soap usage.

An approach based on Hierarchical Context Hidden Markov Model (HC-HMM) is proposed by (Chung et al., 2008) for behavior understanding using cameras located in a nursing home. They represented the behavior into three categorical state definitions: namely spatial, activity, and temporal. For instance, an activity of “walking” is defined within a context of a sequence of “door, sidewalk, bed” and “bed, sidewalk, toilet”. The former behavior could be “a person goes to bed” and the latter behavior could be “a person goes to the toilet”. This was then used to establish a hierarchical HC-HMM which extracts various features associated with the activities using cameras that are distributed through the living space. One of the informative features of the proposed analysis is the usage of the temporal measure by associating the time duration with the probability of the presence of certain activity.

Behavior analysis for an assisted living lifestyle was presented by (Monekosso et al., 2010) that is based on monitoring a subset of Activity of Daily Living (ADL). The experimental setup was developed where each room consists of at least one motion detection sensor, one temperature sensor, one light level detector, and two lighting status sensors (on, off, and light level settings). The monitoring period was over several week-long intervals. The experimental setup also pays close attention to sensing properties such as sensor failure and presence of the noise in the measurements. The behaviors are represented with HMMs. The authors also used an increased number of definitions for hidden states in identifying the performance of the model. However, limitations of this study include a failure to identify how the hidden states are identified and how the performance of the model is defined in terms of the conditional probabilities.

An experimental setup was proposed by (AlBeiruti et al., 2014) to examine if it is possible to infer behavior based on using simple motion detection sensors and a generative model such as HMM. The authors utilize the HMM model to infer the subject’s location in a room based on the associated motion detection sensor. In their modeling assumption, they defined the state to be related to the status of the sensors (which are also used as part of the emission symbols) which were deployed having more than one sensor per monitoring room. Through this approach, their proposed HMM model can also be reduced to a standard Markov Chain due to the coincidence of definitions between the measurements and states.

A comprehensive framework for monitoring activities and vital signs of older adults has been proposed by (Forkan et al., 2015) where they define three hidden states of normal, abnormal, and critical as a part of the hidden states of the system. Although authors have not proposed their own definition of sensor setup for the monitoring environment, they have used publicly available data sets where the presence of the individual in a monitoring room is used as observation. An observable Markov chain was developed where the state of the system was defined based on the activities of the individual. The model is then extended to the HMM where the hidden states were the aforementioned three health levels of the individual. The measurement type which was used to establish a model of the activities is based on motion detection sensors with the recorded activations, deactivations, and duration periods.

A more specific discussion and presentation of the application of HMM for discovering activities of daily living is presented in (Viard et al., 2016). The authors describe that at the time of publication, there had not been any results on methods for configuring the Hidden Chain. Their proposed model was evaluated on an existing database which was obtained through monitoring a dwelling consisting of 77 binary sensors for a two-week observation period. For example, observation in the bathroom was defined through the following switches: exhaust fan, shower facet, sink facet(cold), sink facet(hot), and medicine cabinet. The hidden state was defined as activities that can be performed in the bathroom.

A layered architecture was proposed by (Asghari et al., 2020) where the processing and labeling of the sensor data and recognition of activities were used in a recognition architecture that consists of a hierarchical HMM. In their study, they utilized an existing dataset for monitoring a living space which consists of 32 on/off sensors distributed throughout the living space. They also define 12 hidden states associated with each of the clusters of the monitoring area, for example, bathing, meal preparation, napping, or taking medications.

Using wearable sensors within an indoor wireless network configuration, (Alshamaa et al., 2019) proposed an approach where the strength of the WiFi signals transmitted through wearable sensors within the monitoring area is used to estimate the position of a person. The hidden states were defined as the likelihood of the movement trajectory within the discrete regions of the monitoring area.

Discussion

Establishing a normal baseline of information associated with the healthy movements and activities of an individual is a challenging proposition. This challenge is also compounded by the fact that such information must be inferred from various sensing modalities that are distributed throughout the living spaces. To quantify such information and through consultation with the older adult, family members, health-care providers, and engineers, various utilization and types of sensing technologies need to be considered. Realistic decision-making factors such as costs, protection of privacy, and the expected accuracy of sensors need also to be considered. In this paper, we primarily focused on the usage of ambient motion detection sensors as a sensing modality that can be used to determine the presence or absence of a person within a monitoring area. These sensors are simple and are a low-cost alternative to other sensing technologies in support of aging-in-place which most importantly offers a maximum layer of privacy protection. The paper presented an overview of Markov Chains as one of the main approaches which have been followed in the literature to assist in defining the healthy baseline of movements and activities. Variations of the Markov chains (such as the hidden Markov model) have been suggested for the cases where the deployed sensors can not directly measure the movements and or associated activities of the older adult. Markov Chains have been shown as a possible tool in reinforcing and controlling the monitoring environment for movement or behavior encouragement when anomalies have been detected. Partially Observable Markov Decision Process (POMDP) has been suggested as an enhanced architecture for such reinforcement through interaction with the monitoring environment. In addition to Markov Chains, other forms of movement and activity modeling based on machine-learning and deep-learning have been proposed, e.g. (Hoettinger et al., 2016; Zhu et al., 2018).

Conclusions

Advancement and availability of various sensing/system technologies have allowed us to re-evaluate what can be considered the best alternative in support of various stages of aging-in-place. This paper presents an overview of how the most common types of ambient sensing have been used within the architecture of Markov Chains. This offers an approach to establishing a baseline of movement observations where any future anomalies can be compared. The focus of this overview was motion detection sensors. However, one can anticipate that other types of sensing modalities and system architecture can be incorporated by considering the levels of health, mobility, and personal preferences of the person.

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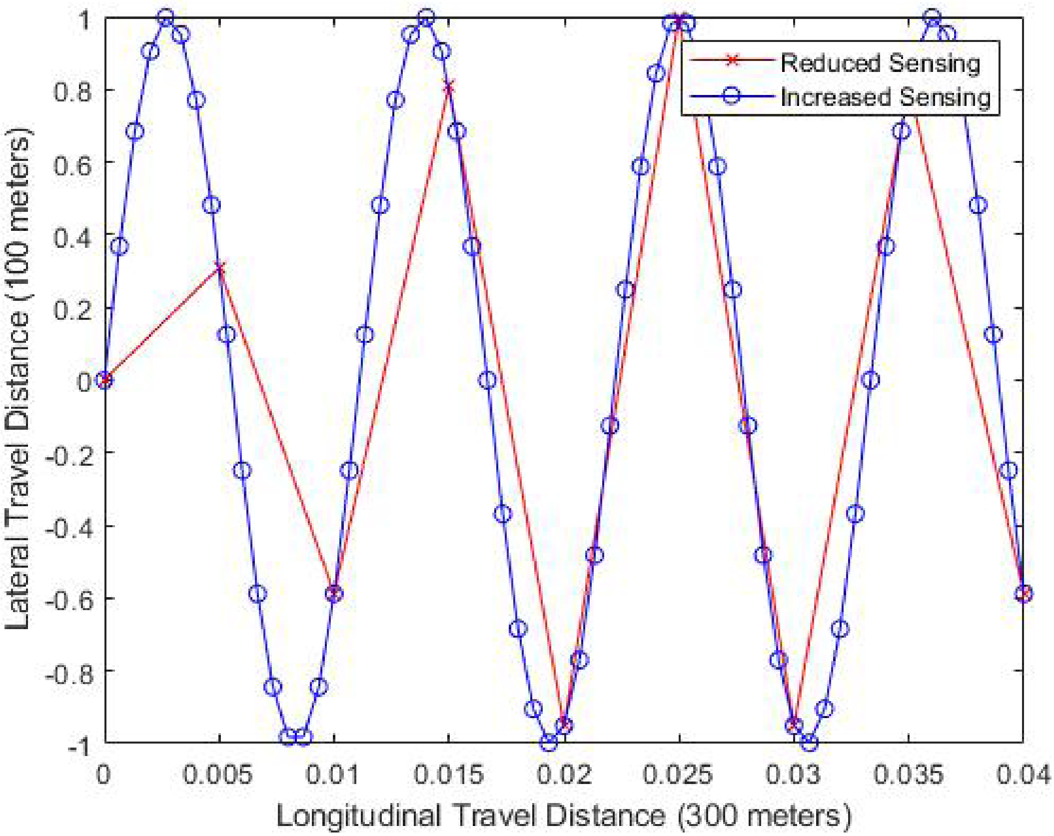

Figure A1. A conceptual demonstration example of estimation the actual movement trajectory of a person. The horizontal axis can be viewed as the longitudinal direction along the hallway whereas the vertical axis can correspond to the direction along the width of the hallway. The sinusoidal path represents the actual trajectory and the small dots along the trajectory represent the location of the sensors.

Appendix

This appendix presents an overview of a basic signal reconstruction through a demonstrative example. It also presents an overview of available motion detection sensing technologies and the associated opensource integration software for automation of the monitoring environment.

A simple example of trajectory reconstruction

This appendix gives a simple interpretation of challenges associated with tracking and estimating movements using elementary observation from the sampling theorem. *Figure A1* shows a conceptual sinusoidal path which is a representative of a movement of a person along a hallway and small circles along the path represent the locations of the motion detection sensors. These sensors are assumed to only detect the presence of a person when the person is directly over the sensors (i.e. there are no interferences between the sensors). As it can be seen, when the number and the location of these sensors are reduced,

Table A1. A list of available ambient motion detection sensors and their basic properties.

Manufacturer	Range	Time delay	Web address
Aeotec motion sensor	16 ft with 120 FOV	240 sec	https://aeotec.com/smartthings/zigbee-motion-sensor.html
Phillips Hue Motion sensor	16 ft with 100 FOV	15 sec	https://www.philips-hue.com/en-au/p/hue-motion-sensor/8719514342149#overview
ZsE18 S2 Motion sensor	25 ft with 100 FOV	30 sec	https://www.getzooz.com/zooz-zse18-s2-motion-sensor/
Ikea Tradfri Motion sensor	15 ft with 120 FOV	120 sec	https://www.ikea.com/ca/en/p/tradfri-wireless-motion-sensor-white-60377655/
Sonoff SNZB-03 Motion sensor	20 ft with 100 FOV	60 sec	https://sonoff.tech/product/smart-home-security/snzb-03/
HomeSeer HS-MS100 Motion sensor	12 ft with 90 FOV	60 sec (adjustable)	https://shop.homeseer.com/collections/z-wave-sensors/products/z-wave-motion-sensor

Table A2. Open-source home monitoring platforms

Brand	Web address
Home Assistant	https://www.home-assistant.io/
openHAB	https://www.openhab.org/
Pytomation	http://www.pytomation.com/
OpenRemote	https://openremote.io/
Calaos	https://www.calaos.fr/en/
OpenMotics	https://www.openmotics.com/en/
Domoticz	https://domoticz.com/

the estimated trajectory of the person becomes very coarse, the estimated trajectory is far from the actual sinusoidal trajectory. This experiment demonstrates the fundamental challenge associated with movement estimation of older adults in their place of residence using only motion sensors.

Standard Properties of ambient motion detection sensors

For many decades, ambient motion sensors have been used as one of the well-proven technologies for home security and have been available through various home security service providers. These sensors utilize, on/off switches which can be placed at various locations in monitoring areas. In recent years such technology and in its wireless form has become widely available as an affordable commodity product. In addition, various free resources have been developed which allow easy integration of these sensors as a part of the home monitoring system (Smart Home). In this section, we first highlight some of the main features of these commercial motion detection sensors and then the list of available and open-source, sensor integration environments.

Here we first present various technologies which have been used to detect motion and then we list some of the main vendors of the motion detection sensors. We also list some of the key features of these sensors which need to be considered when integrating them within a sensor network monitoring environment. Since most of these sensors are battery-operated, attention needs to be paid in selecting and adjusting sensitivity as a function of delay trigger time settings.

- Passive Infrared Sensor (PIR) – Detects warm bodies as they pass by. For example, walls, floors, stairways, and windows radiate some amount of heat. Infrared motion sensors detect the presence of a person or object by detecting the change in temperature in each area.
- Ultrasonic Sound Waves (USW) – Transmits and detects frequency above the range of human hearing. These waves bounce off objects which are in the immediate vicinity of the sensor and return to the motion sensor. A transducer sends the pulse and receives the echo. The sensor determines the distance between itself and the target by measuring the time.
- Microwave (MW) – Similar to an ultrasonic sensor (USW), the microwave wave bounces off objects and returns to the sensor. It can cover a larger area with respect to the ultrasound sensors. They are more susceptible to electronic interference.
- Tomographic Motion Sensors – It uses a network of USW-based distance sensors to detect the presence of humans based on changes in the baseline signal strength between nodes. Such a system can enable detection by also passing through walls.
- Vibration Sensors – These sensors as the name implies can be tuned to detect the presence of movement through the detection of vibration within their mounting environment.

Motion detection

The following highlights some of the technical features of commodity sensors. One of the main

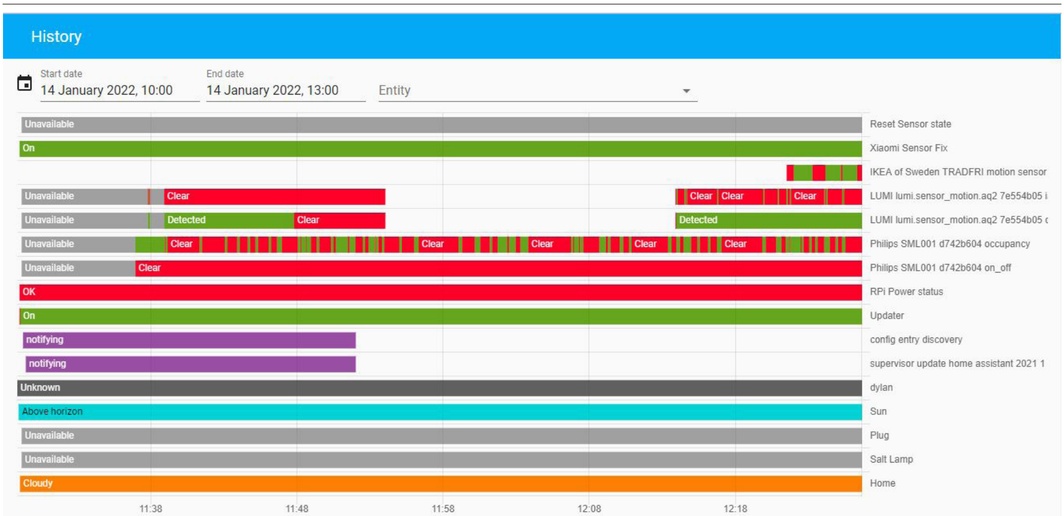

Figure A2. A representative log-page of motion detection consisting of Ikea, Lumi and Phillips motions sensors.

features which may play an important role is the time delay associated with each sensor. This implies that even if the person has moved away from the detection range of the sensor, the sensor still indicates motion for the duration of its delay. For example, a person can move between the rooms while the motion sensors of each room can still trigger and indicate that the person is in both rooms. The other technical feature is the field of view for their effective detection and how they are positioned with respect to the monitoring areas (*Table A1*).

Open-Source monitoring platforms

In this section, we present a list of available open-source home monitoring systems which can be configured and deployed on any available computational platforms. These environments can be configured and networked with wireless motion sensors as a part of the movement monitoring system (*Table A2*).

These platforms can be configured and deployed on any basic computing hardware such as raspberry pi with the paired z-bee dongle and the wireless motion sensors. The platform can associate each of the sensors to the corresponding monitoring area. A Typical platform can store the log data in a format of having the beginning and the end duration as a function of the activation signals obtained from the motion sensor. The stored data can then be processed to obtain the statistical distributions in a form of conditional probabilities for a given window of observation. *Figure A2* shows a typical screenshot of the log page for a test period involving four motion sensors.